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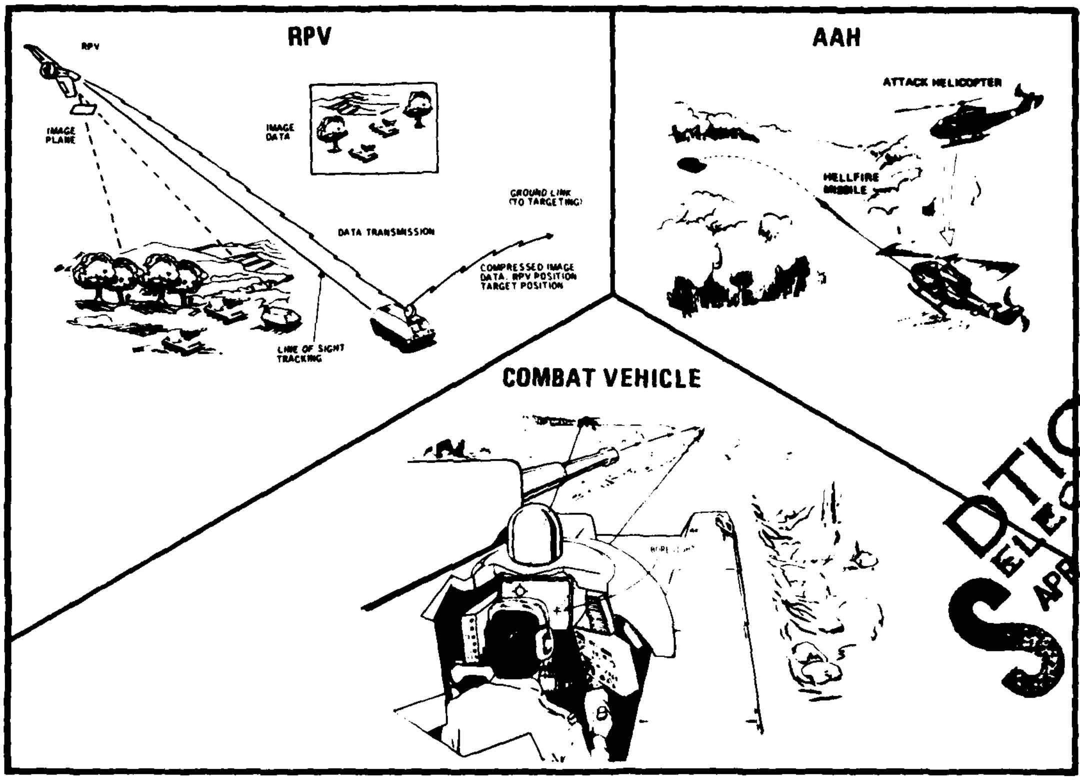

THIRD QUARTERLY PROGRESS REPORT

1 APRIL TO 30 JUNE 1980

Prepared for
UNITED STATES ARMY
Night Vision and Electro-Optics Laboratory
Fort Belvoir, Virginia 22060

Honeywell

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Conventional target tracking approaches rely on numerical correlation over successive frames on a window around the target. They are therefore sensitive to partial obscuration and changes in target and background appearances. Furthermore, multiple-target tracking requires replication of the hardware.

In this third quarterly report, we present the results of the continuing development of a multiple-target tracking approach based on a dynamic scene model derived -

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from the analysis of a time sequence of imagery. Simulation results demonstrate multiple-target tracking in cluttered backgrounds and in imagery from fast-moving platforms. The approach can be implemented as an integral part of the Honeywell target screener system.

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SECTION 1

INTRODUCTION

This is the Third Quarterly Progress Report on Advanced Target Tracker Concepts, NV&EOL Contract No. DAAK70-79-C-0150. It reports the results of the work performed between 1 April 1980 and 30 June 1980.

Tracking targets in video from TV and FLIR sensors is essential for fire control in weapon systems using electro-optical target acquisition. Typical Army applications include the remotely piloted vehicle (RPV), the advanced attack helicopter (AAH), and the combat vehicle (CV). Target tracking in these applications yields the target position for accurate pointing of a laser designator for a smart munition, such as Hellfire and Copperhead, or for fire control of conventional weapons.

Currently fielded trackers rely on numerical correlation over successive frames on a window around the target to be tracked. Several variations of the basic correlation scheme exist, and a detailed survey can be found in "Assessment of Tracking Techniques."[1] Conventional trackers are capable of tracking a manually acquired single target in relatively clutter-free backgrounds. However, target tracking requirements for the increasingly sophisticated weapon systems have grown beyond the capabilities of the current correlation trackers.[1]

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[1] B. Reischer, "Assessment of Target Tracking Techniques," Proceedings of SPIE, Vol. 178, Smart Sensors, pp. 67-71, 1979.

In this program Honeywell Systems and Research Center is developing an advanced target tracker approach, based on dynamic scene analysis, which will satisfy these requirements. This approach integrates the target screening and tracking functions which can provide automatic acquisition and multiple-target tracking through low signal-to-noise and high clutter conditions. This is done with a target screener and minimal additional hardware.

Figure 1 is an overview block diagram of the basic approach which builds the advanced tracking function upon the scene analysis functions performed by the target screener. The basic premise is very simple: the target screener segments and classifies significant objects (targets and clutter) in real time on a frame-by-frame basis. Symbolic descriptions of the objects in each frame are used to find the corresponding objects in previous frames encompassing the history of the scene.

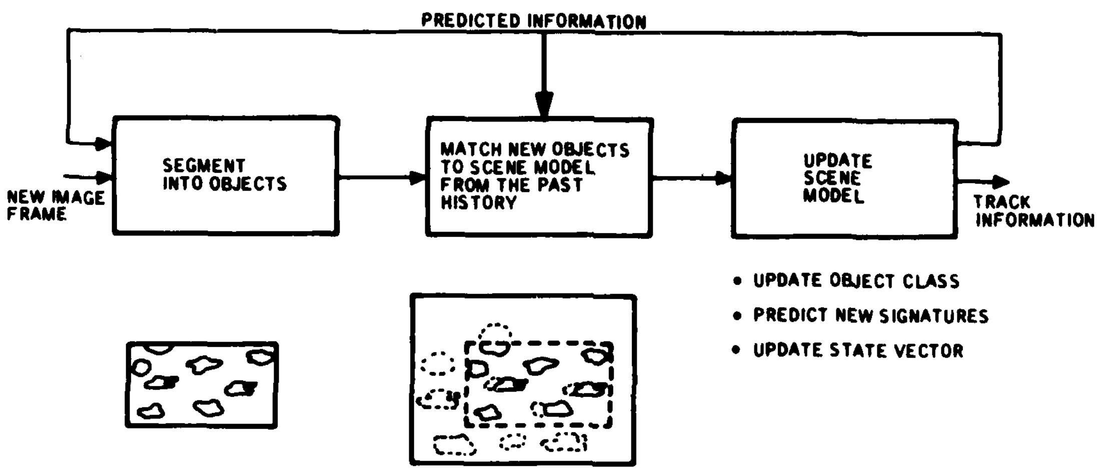


Figure 1. Overview of the Advanced Target-Tracking Approach

Once the corresponding object matches are made, the scene model, which includes the sensor and object dynamics as well as the target classes, is updated. Because we are keeping track of the positions of all the objects in the scene (targets and clutter), we can predict impending occlusion and future target/background signatures. Multiple-target tracking, of course, comes free. The scene model, based on the past history of the scene, can extend beyond the current field of view. This allows reacquisition and tracking of targets which wander in and out of the field of view because of sensor platform motion.

A complete block diagram of the major functions necessary to implement the advanced target-tracker concept is shown in Figure 2.

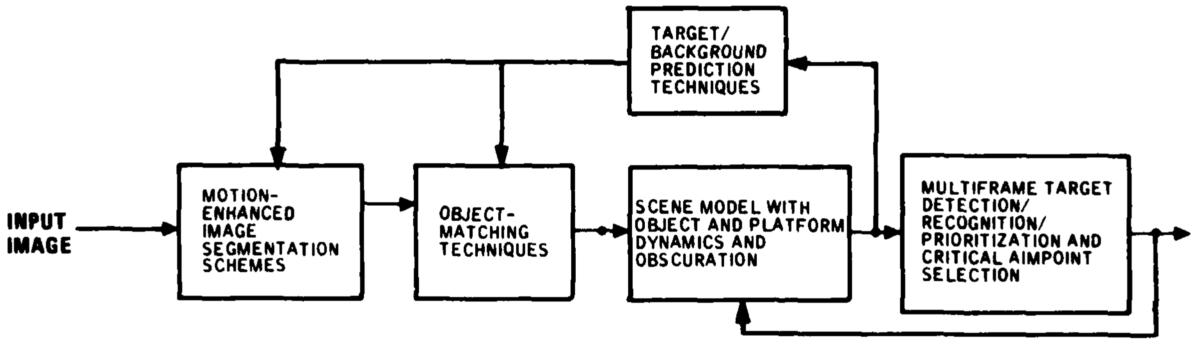


Figure 2. Advanced Target Tracker Program Overview with the Key Functions

The functions representing the major thrusts of the current program are:

- Efficient motion-enhanced scene segmentation schemes,
- Object-matching techniques capable of precise matching of objects in the new frame to the scene model derived from previous frames,
- A scene model capable of characterizing object and platform dynamics, target/background signatures, and object occlusion,
- Target/background signature prediction techniques to improve the probability of target acquisition in low signal-to-noise ratios,
- Advanced target detection/recognition/prioritization and critical aimpoint selection algorithms which can exploit the dynamic multiframe information.

The details of the basic approach and the previous results are documented in the earlier quarterly progress reports.

SUMMARY OF PROGRESS

Following is a summary of progress made during the third quarterly reporting period:

- Algorithms for updating the scene model based on the silhouette matcher output have been developed.
- Velocity estimation and shape prediction algorithms have been incorporated into the system simulation.

- A 200-frame sequence from the March 1980 flight test of the Honeywell Prototype Automatic Target Screener (PATS) has been digitized and segmented using the PATS system.
- The tracker simulation has been run on a portion of the 200-frame sequence. It successfully tracked maneuvering targets through several occlusions.
- A video tape containing half an hour of moving target imagery was edited from a number of FLIR video sources. This tape will be transferred to an MCA video disk. When completed, we will be able to process every frame (30 Hz) in a near-real-time processor (for example, PATS) operating in "snap-shot" mode.

REPORT ORGANIZATION

The remaining sections of the report are organized as follows:

- Scene Model
- System Simulation
- Data Base
- Plans for Future Reporting Periods

SECTION 2

SCENE MODEL

The primary functions of the scene model are to keep track of and infer information about objects in the scene as well as the platform dynamics derived from the analysis of the previous frames. More specifically, the scene model comprises:

- Platform dynamics (position and velocity)
- Individual object models, including object dynamics and shape
- Occlusion prediction
- Shape prediction
- Background prediction

In previous reporting periods we developed techniques for estimating the platform dynamics between frames, using the object matches in those frames. Using these techniques we have successfully demonstrated that scene motion can be estimated to within a few pixels. We have also shown that, after compensating for platform motion, a moving target can be easily distinguished from stationary clutter. We have also developed a data structure which can represent objects and the relationships between objects. The data structure allows the efficient handling of occlusions, missegmentations, and multi-component targets, as well as the storing of velocity, shape, and other object features.

OBJECT MODEL

In this reporting period we have developed algorithms for incorporating the output of the silhouette matcher into a useful model of the objects in the scene. Each object model includes the following features:

- Area
- Contrast
- Velocity (after compensation for platform dynamics)
- Position
- Shape
- Consistency

The object models we construct become part of the overall scene model and have a variety of uses within the tracking system. They are used for predicting position in the matching routines, coasting object positions when the object is improperly segmented, and recognizing occlusion. The model update algorithms and uses of the object model will be discussed in subsequent paragraphs.

OBJECT MODEL UPDATE STRATEGY

The object model update routines use the matching relations determined by the silhouette matcher to update the object models. The output of the silhouette matcher includes not only links between matching objects but also the position and velocity of the object as determined by that match.

VELOCITY UPDATE

The velocity is the displacement required to precisely align an object model with an extracted segment after accounting for scene motion. These velocities are averaged over several frames to give the velocity of an object model.

The stored position and velocity values are used to predict the position of an object in the current frame. The predicted position is then used as a starting point for the silhouette matching algorithm.

Previously, the predicted position of an object model was defined as the position of the model in the previous frame, transformed into the current frame coordinate system. The transformation was determined by the matches given by the simple feature matches. This technique is adequate if the objects are stationary relative to the rest of the scene.

However, if the objects have moved, relative to the scene, they may fail the prerequisites for silhouette matching. This will cause us to lose track of moving objects by failing to match an object model with an extracted segment. We can achieve a better alignment of moving objects by using the velocities stored in the object model. The object velocity is added to the current position and then transformed into the current frame coordinate system by a transformation determined by the simple feature matches.

It is possible to make this prediction since the velocity stored in the model is independent of the scene motion. So, even in the presence of extreme sensor motion we will be able to accurately predict the location of a moving object in the current frame.

This same technique is used to predict the location of objects which have not been matched in the current frame. Since the velocity of the object model is independent of sensor motion, we will be able to coast positions for many frames and still maintain an accurate estimate of the object's position. This is necessary when a moving target is completely occluded or has left the field of view.

SHAPE PREDICTION

The shape which is stored in the model for consistent objects is the most recently segmented shape for that object. However, if there is a large difference in the segmented shape of the model and the shape of a matching object, then the stored shape is not updated. In this manner tentative segmentation errors due to noise will not affect our stored shape. On the other hand, if the object has indeed changed shape because of a change in aspect, then we must replace the stored shape or else we will not have an accurate shape model. This is done by replacing all shapes which are very stale (say, older than five frames). Thus, if an object changes its shape and continues to be different from the object model (for say, five frames), the object model will be updated to the new shape. The area and contrast of the object model are updated only when the shape is updated. These

features are functions of the particular segmentation and should not be updated when we have a questionable segmentation (that is, the shape of the model and extracted segments do not match).

CONSISTENCY CRITERION

In running the system simulation on the 200-frame sequence, we found that only a small set of objects in the scene were consistently segmented over many frames. This set of consistently segmented objects included the targets as well as some prominent background objects. Inconsistent segments included low contrast objects in the background and segmentation anomalies. Clearly, a knowledge of the consistent objects would be valuable to the tracking system. For example, since targets are included among the consistent objects, we could apply complex target recognition and velocity estimation algorithms to the small set of consistent objects rather than to every object in the scene. This results in a considerable decrease in the computational complexity.

In our object model the consistency of an object is determined by a counter. It has a value between 0 and C_{max} (currently 15). The counter is incremented with each one-to-one match that is found for the object and decremented when no match is found for the object. It remains unchanged if the object is involved in anything except a 1:1 or 1:0 match. Those objects with high counter values have been involved in many one-to-one matches and can be considered "consistent objects". In the current simulation any object with a counter above ten is considered consistent.

Consider the segmentation sequence shown in Figure 3a-d. These are four frames from the beginning of the 200-frame sequence. Most of the objects in the scene are not consistently segmented. They appear in one frame as one object and then break up in the next frame. In Figure 3e we have outlined the consistent objects for the first 10 frames of the sequence. These objects are the only ones which have been consistently segmented in the first 10 frames.

Consistent objects are given special consideration when we update the object models. In general, we try to retain consistent object models even though they may exhibit some short term inconsistencies. On the other hand, inconsistent objects are deleted from the object model list unless a one-to-one match for them is found.

OBJECT OCCLUSION

The shape, consistency, position, and velocity features are all used to recognize occlusions and perform shape prediction. This allows the tracker to maintain track of targets which are occluded by other targets or which have been obscured by background objects.

Occlusions are recognized by finding those object models involved in many-to-one matches. Some of the many-to-one matches are caused by the breakup of large background regions by the segmentation algorithm. Other many-to-one matches are caused by targets moving and occluding other objects in the scene. We distinguish between these two cases by using the consistency measure; any many-to-one match which involves

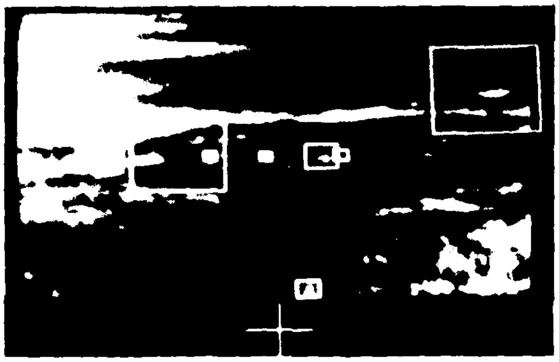
a. Frame 2 Segmentation

b. Frame 4 Segmentation

c. Frame 6 Segmentation

d. Frame 8 Segmentation

Figure 3. Consistent Object Determination. Only those objects outlined in Figure 3e have been consistently segmented in the first 10 frames.



e. Consistent objects over the first 10 frames

Figure 3. Consistent Object Determination (concluded)

a consistent object is assumed to be an occlusion while many-to-one matches between inconsistent objects are not.

When one object is occluded by another, some or all of its edges will not be visible in the current frame. Our silhouette matcher will be unable to accurately locate an object without visible edges in the current frame. The matcher may not find the correct position of an object with only some visible edges. It is the function of the shape prediction algorithm to determine which edges of the object will be visible. If it is found that no edges will be visible in the current frame, then no silhouette matching will be performed for that object. If some of the edges will be visible, then the silhouette matcher is instructed to match only the visible edges.

This technique is demonstrated in Figure 4. The left-hand column contains the object models from three hypothetical frames. In Frame 1, the two objects are not occluding one another, so there is no predicted shape for the next frame. The segmentation for the next frame is shown in the right-hand column. Note that the two objects are now partially obscured. The occlusion is recognized in the second frame and the visible edges are identified for the third frame. The silhouette matcher will be instructed to use only those edges in matching with the third frame segmentation. Similarly using the positions, velocity, and shape features of the Frame 3 models, we identify the visible edges in Frame 4 and match only those edges.

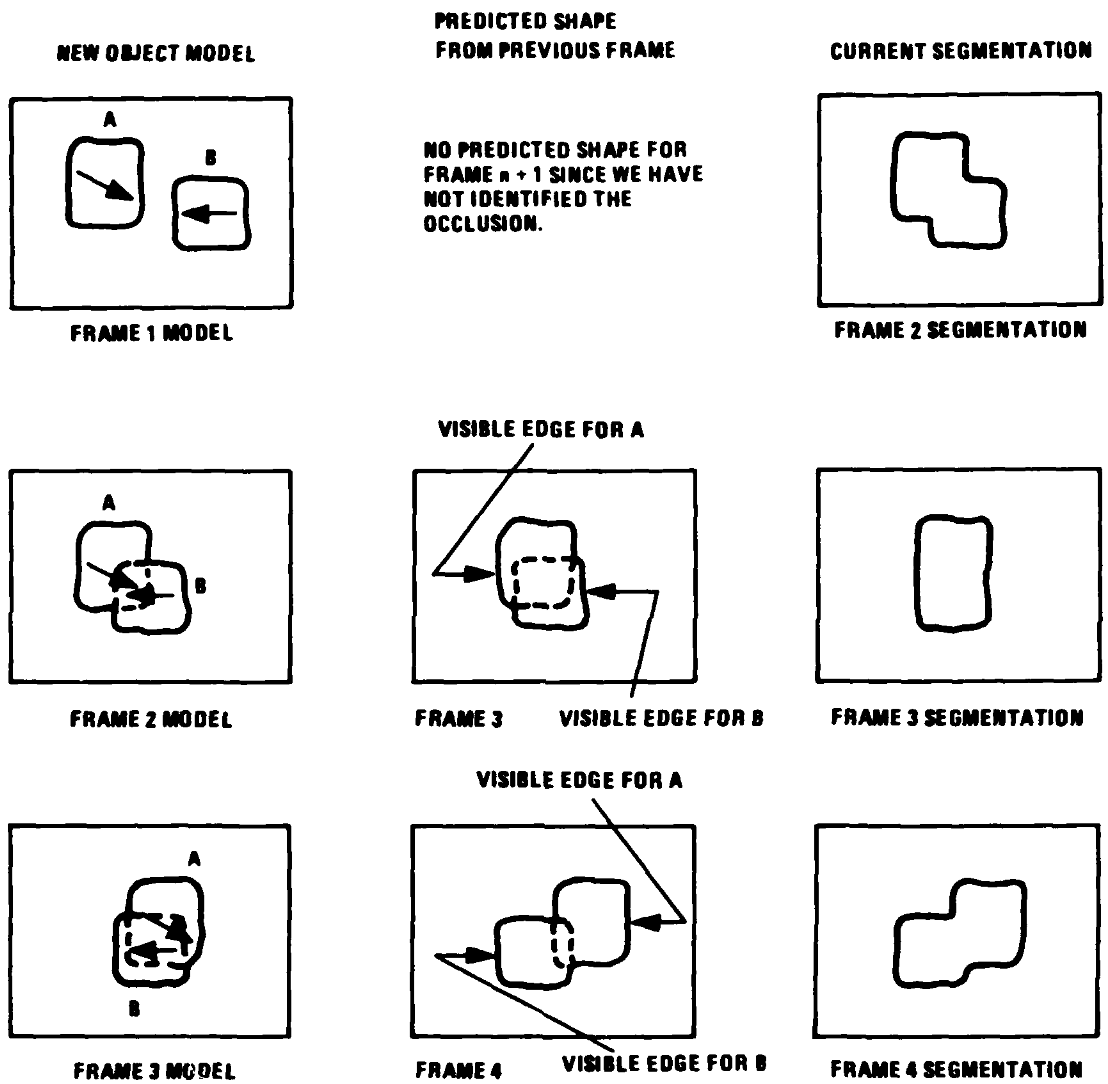


Figure 4. Occlusion Recognition and Shape Prediction

SECTION 3

SYSTEM SIMULATION

The techniques which have been developed during this reporting period have been incorporated into a complete system simulation of the advanced target tracker system in the Honeywell Image Processing Facility. This simulation allows the evaluation of the algorithms as they are developed in the system context. This system simulation will be expanded as new algorithms and software are developed for such factors as critical aim-point selection, target/background signature prediction, and advanced scene models.

A block diagram of the current system simulation is shown in Figure 5. The simulation currently consists of the following software modules:

- PATS segmentation
- Simple object matching
- Scene transformation
- Fast silhouette matching
- Model update
- Model prediction

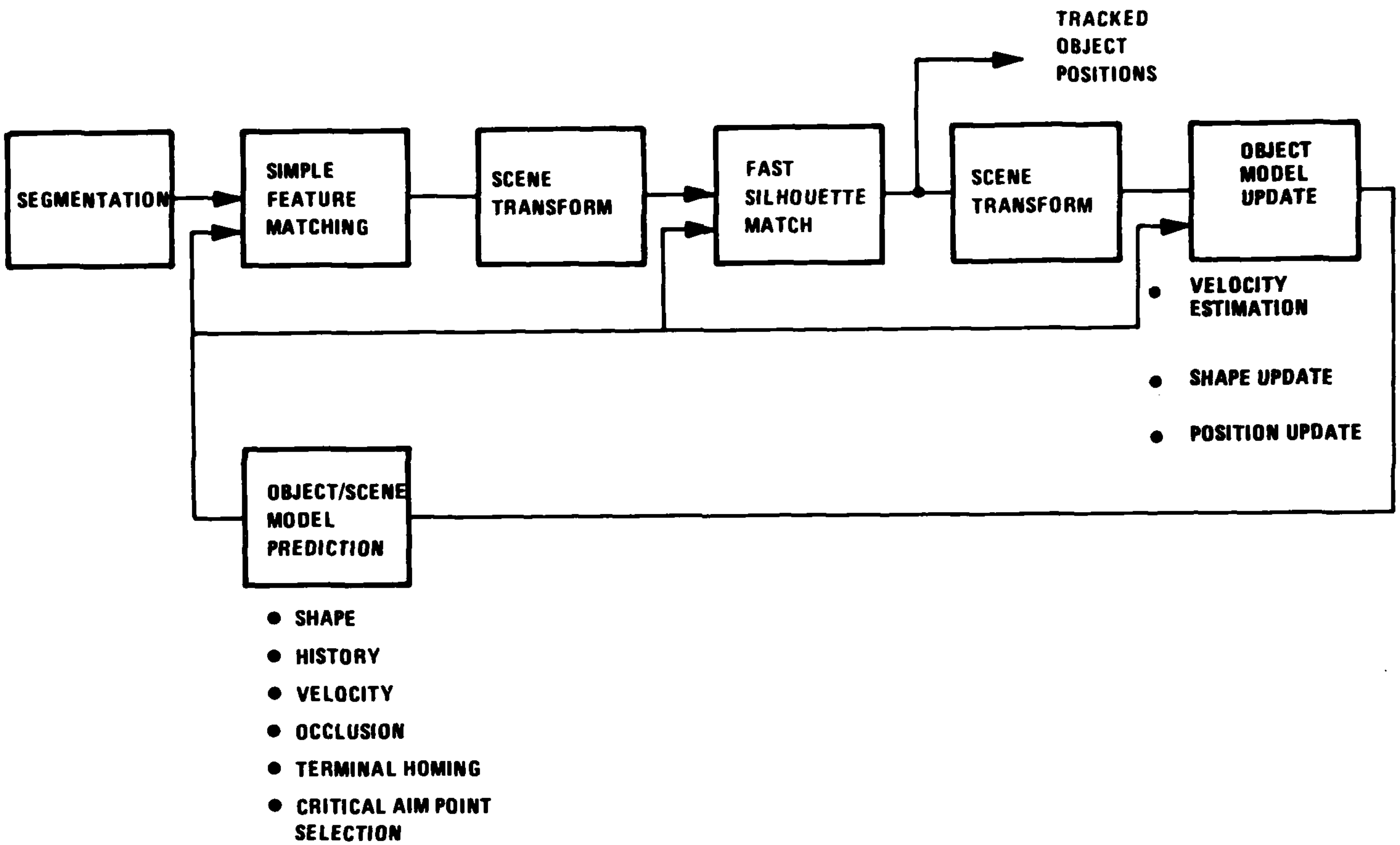


Figure 5. Current State of System Simulation

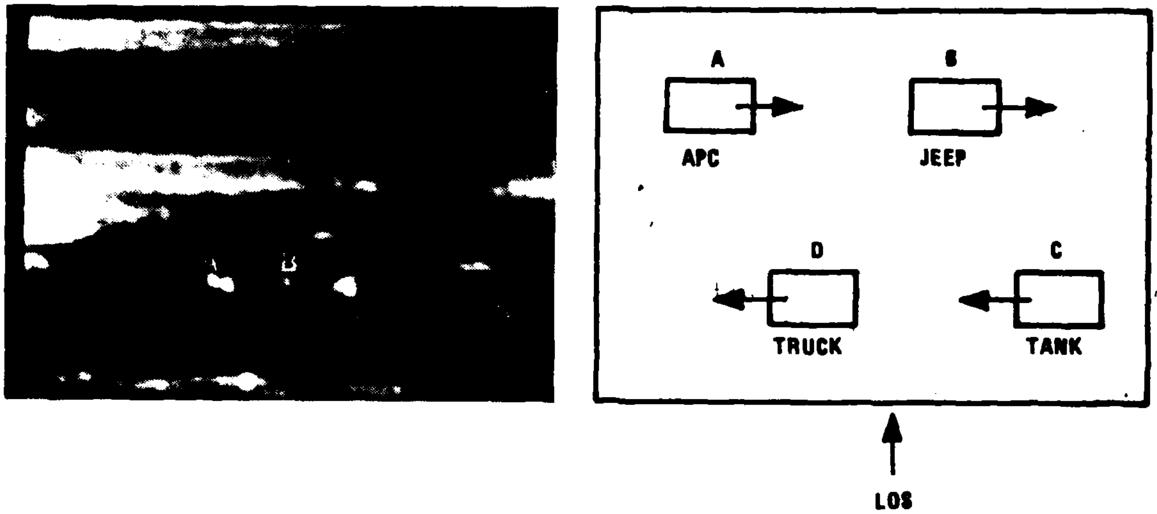
In the system simulation, the PATS segmentation is applied to an input frame. This produces a list of object outlines and features which are to be matched. The object matching algorithms match the outlines and features of the object models against those of the segmented objects. The simple feature matcher rapidly finds those objects which have an exact match in the current frame. These matches determine a transformation which is used by the fast silhouette matcher to find a starting point for the matching process. The output of the object matching routines is a list of object matches and the positions and velocities determined by that match.

During this reporting period the object model update and prediction routines, described in the previous section, have been implemented. Also during this period we have run the simulation on a portion of a 200-frame sequence from the March flight test of PATS. This sequence contains multiple maneuvering targets in a cluttered background. It also contains several interesting examples of target occlusions. The subsequent paragraphs describe the sequence and the results.

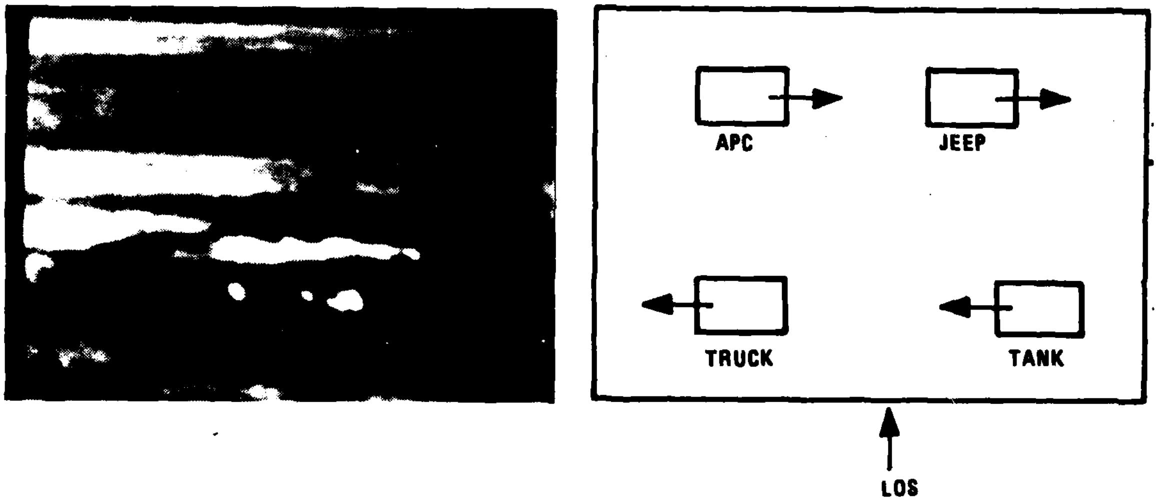
TEST SEQUENCE

We have digitized and segmented a 200-frame sequence from the March PATS flight test. The frames were recorded at 10 Hz and every frame processed in order to simulate real-time operation of the tracker.

This sequence presents some challenging tracking scenarios. Consider the sequence in Figure 6. These magnified views show four targets, as seen by the FLIR sensor, and a diagram of their positions as seen from overhead.

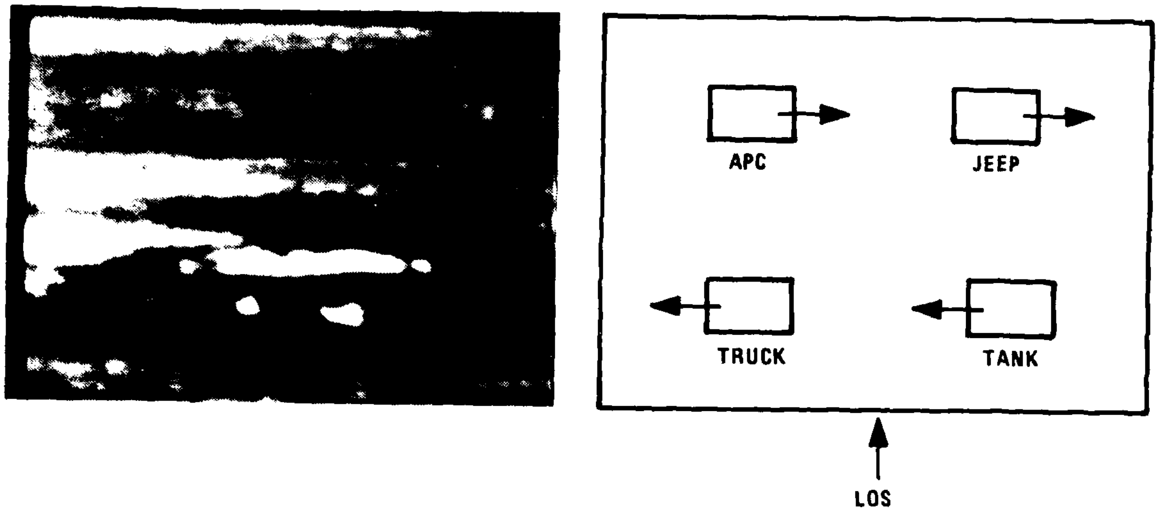


a. Frame 96. Four targets are visible.

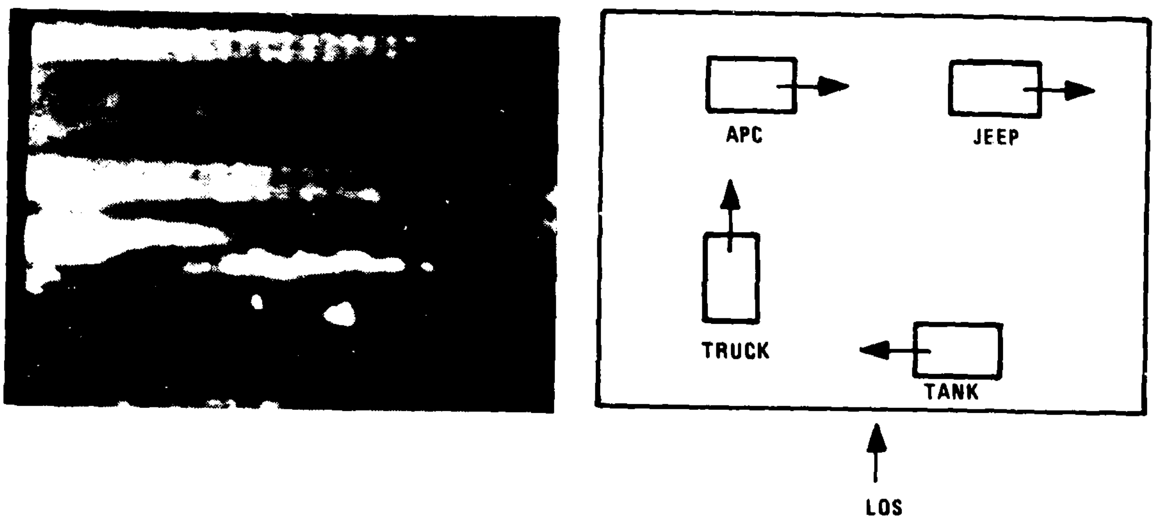


b. Frame 101. The truck has occluded the APC in this frame.

Figure 6. A Challenging Tracking Problem Contained in the Tracking Test Sequence. Each of the following figures contains a magnified view of a window around the targets as well as a diagram of the target positions as seen from overhead.

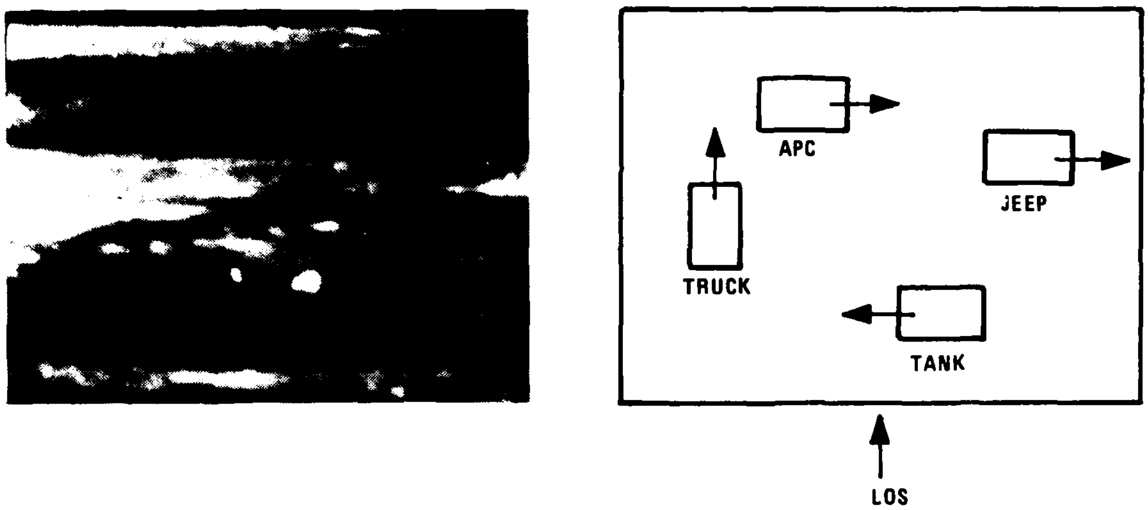


c. Frame 106. The tank has occluded the jeep in this frame.

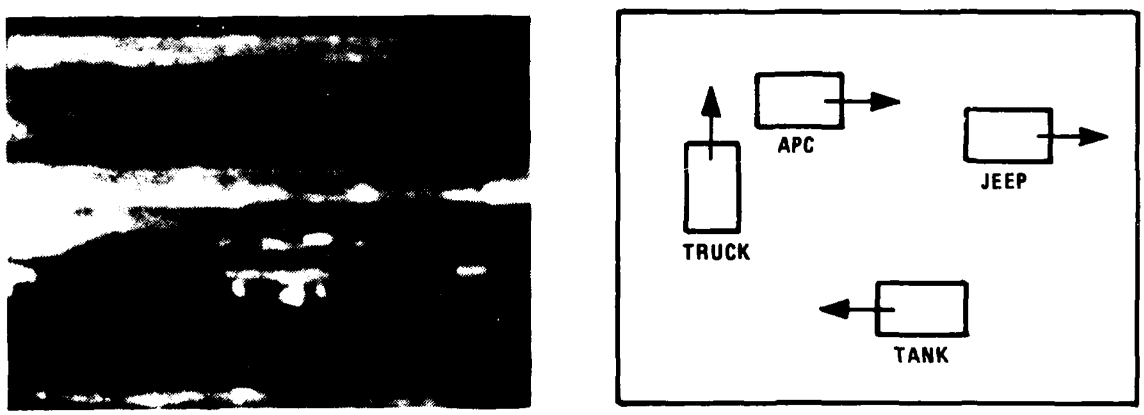


d. Frame 111. In this frame, the truck has turned so that the hot engine is no longer visible to the sensor.

Figure 6. A Challenging Tracking Problem Contained in the Tracking Test Sequence (continued)

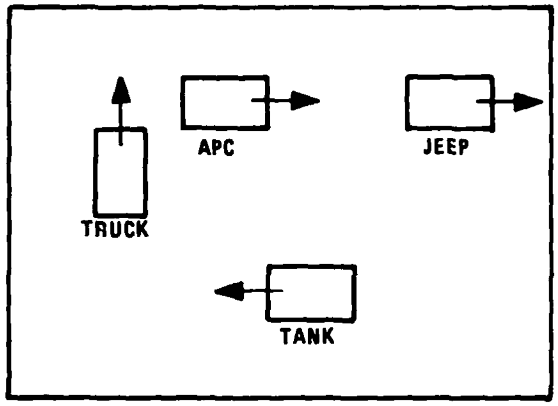


e. Frame 116

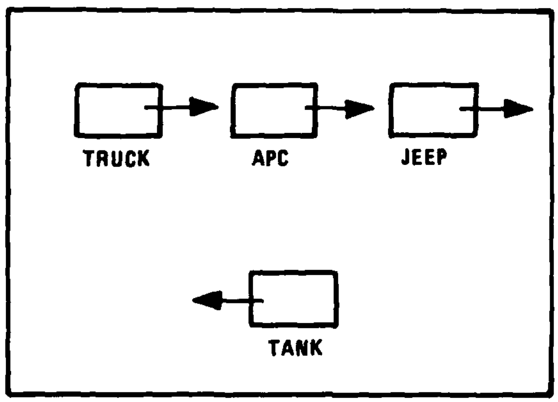


f. Frame 121. The jeep is now detected to the right of the tank.

Figure 6. A Challenging Tracking Problem Contained in the Tracking Test Sequence (continued)



g. Frame 126



h. Frame 131. The truck is clearly visible to the left of the APC and tank.

Figure 6. A Challenging Tracking Problem Contained in the Tracking Test Sequence (concluded)

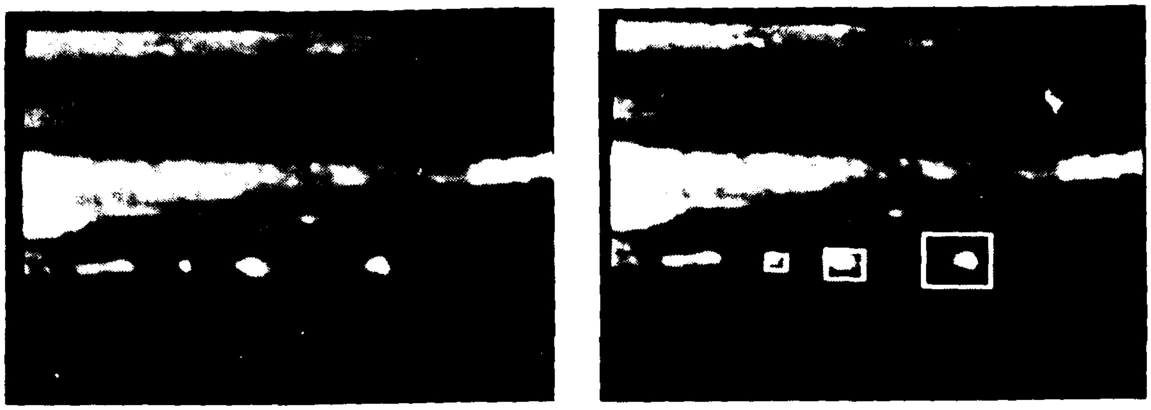
In frame 96, four targets, tank, APC, truck and jeep are all visible. In frame 101, the truck and APC have advanced and the truck is occluding the APC. In frame 106 the jeep and tank have now occluded one another. In frame 111 the truck has turned so that its engine is no longer visible to the sensor while the tank and APC are still visible. The tank and APC are still the only targets visible in Frame 116. In frame 121, three targets are again visible, the tank, jeep and APC. The truck, however, is still not detected since its engine is not visible to the sensor. Finally, in frame 131 the truck is again visible while the tank and APC have occluded one another. This sequence demonstrates the problems of multiple target occlusions as well as background clutter and scene motion.

We have processed 120 frames through the simulation at this time. The results of some of the more interesting sequences are shown in Figures 7 and 8. The sequence in Figure 7 shows the APC occluding the jeep. At this point in the sequence the jeep had not been declared a consistent object. Therefore, no track box appears about the jeep. In frame 61 we see the APC within the track box and, to the left of the APC, we see the jeep. Several frames later, frame 71, the two targets appear as one blob in the image. However, notice that the track box for the APC remains centered on that target. Later in frame 91 the jeep reappears but does not affect our tracking or either the APC or the tank.

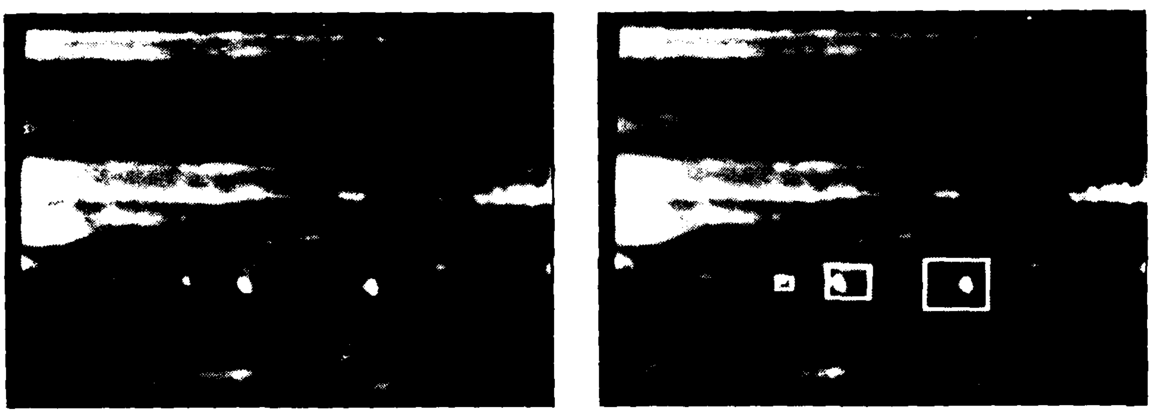
a. Frame 61. Before and after processing. Boxes have been placed around selected consistent objects in order to show the results of the tracker simulation. The boxes surround, from left to right, a truck, APC and tank. Between the APC and truck is a jeep which has not been detected by the simulation.

b. Frame 66. The jeep has not been declared a consistent object; therefore, no box is drawn around it.

Figure 7. Advanced Target Tracker Simulation Results

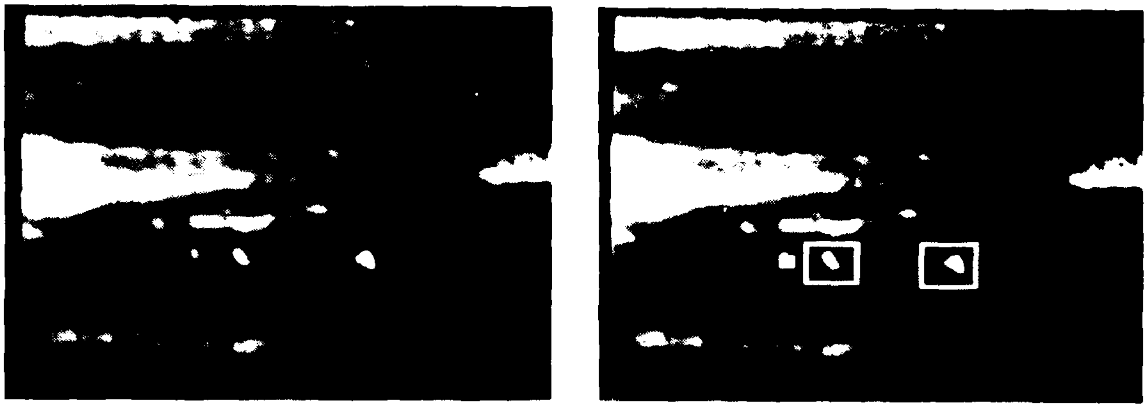


c. Frame 71. The APC has occluded the jeep and a consistent track is maintained on the APC.



d. Frame 76. We continue to track the APC while it is occluding the jeep.

Figure 7. Advanced Target Tracker Simulation Results (continued)

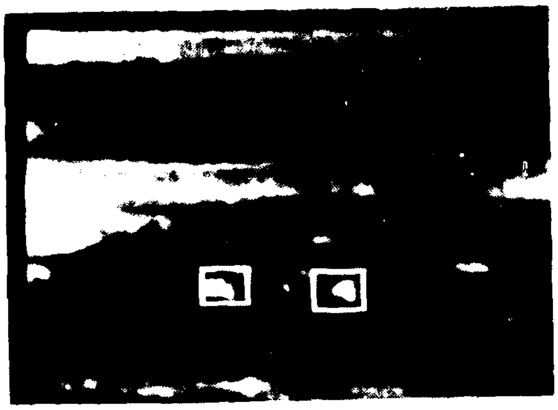


e. Frame 81. The visible edges of the APC are matched in order to track it through the occlusion.

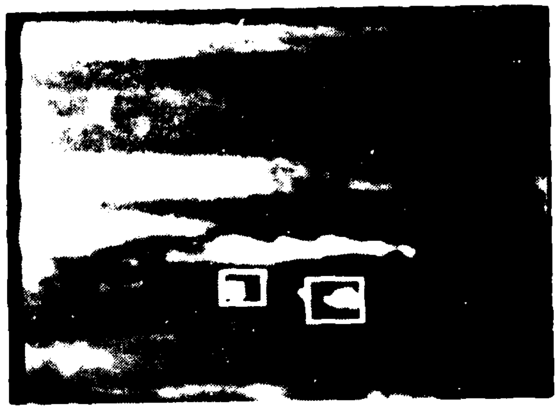
f. Frame 91. The jeep reappears to the right of the APC. This does not affect the tracking of the APC.

Figure 7. Advanced Target Tracker Simulation Results (concluded)

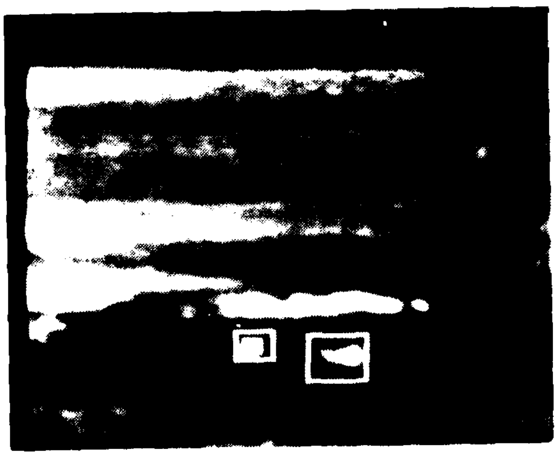
We have also processed the sequence in Figure 6. The results are shown in Figure 8. Several target occlusions are represented here. In frame 96 three targets are shown within the track boxes. In frame 101, even though the truck and APC appear as one blob, the tracker maintains two distinct object models. In subsequent frames the visible edges of the model are matched against the edges of the blob. The boxes for the truck and APC continue to merge in frames 106-126. In frame 121, we would expect to see the truck reappear from the left side of the APC. Unfortunately the truck has turned so that it cannot be detected. Therefore, when the tracker attempts to match the left edge of the shape model of the truck against the segments in the image, it incorrectly matches against the left edge of the APC. This is shown in frame 126 where the truck and APC symbols are both on the same blob. The truck reappears in frame 131. At this time it cannot be matched to the model which is some distance away.



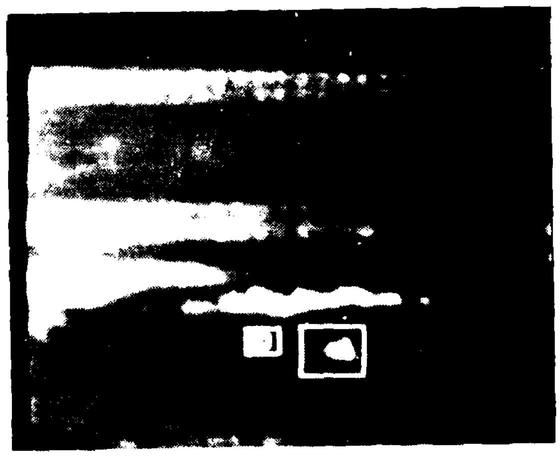
a. Frame 96. The symbols for both truck and APC are centered on the correct targets in this view.



b. Frame 101. The truck has occluded the APC. Both symbols are aligned on the same blob.

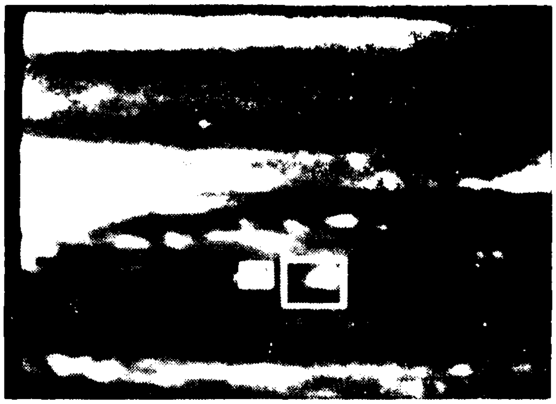


c. Frame 106. We continue to track both objects.

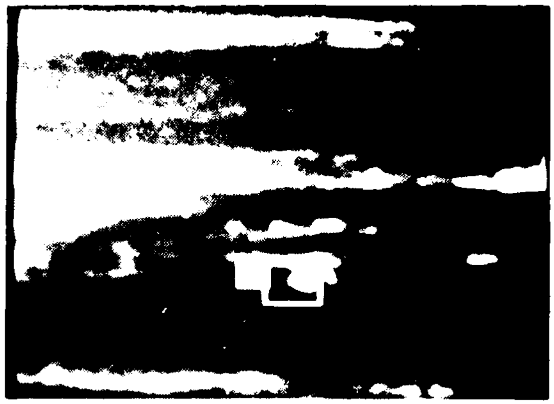


d. Frame 111

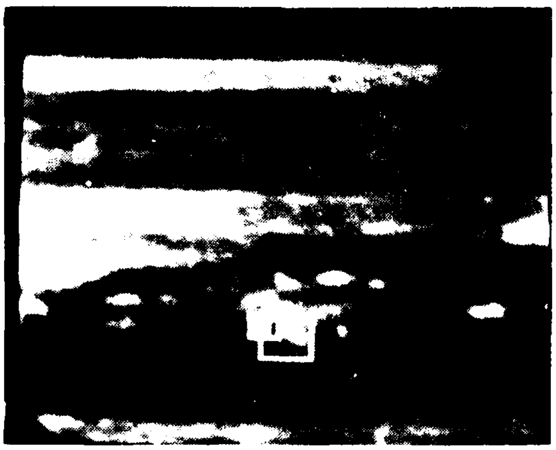
Figure 8. Results of Tracker Simulation Applied to the Sequence Shown in Figure 6



e. Frame 116. Note that the tank has occluded the jeep in this frame. It does not affect the track box for the tank.



f. Frame 121. The reappearance of the jeep to the right does not affect the tracking of the tank.



g. Frame 126. The model of the truck is incorrectly matched to the APC since the truck did not reappear.

h. Frame 131. The truck has reappeared, but it is too far from its expected location to be matched.

Figure 8. Results of Tracker Simulation Applied to the Sequence Shown in Figure 6 (concluded)

SECTION 4

DATA BASE

This section summarizes the continuing data base generation effort. An extensive FLIR video tape library of tactical targets in various backgrounds exists at Honeywell, acquired from NV&EOL and other sources. Our approach to the selection and digitization of sequences for simulation is evolutionary. As new algorithms are developed, we will select image sequences which contain features suitable for algorithm evaluation. Previously we have digitized sequences of moving targets from high speed platforms to test our platform dynamics estimation. In this reporting period we have digitized a 200-frame sequence from the March PATS flight test. This will be used to evaluate our object model, occlusion recognition, and shape prediction algorithms. Examples from this sequence appear in the previous section.

Also during this reporting period, from our video tape library, we have recorded a half hour video tape which contains interesting sequences of moving targets. This tape includes tanks, APCs, jeeps, and trucks from all aspects and ranges from 0-8Km, in both cluttered and clear backgrounds. This tape will be transferred to an MCA video disk. This disk can be played back in Honeywell's Image Research Laboratory. Individual frames can be displayed and processed. In this manner real-time operation can be simulated.

SECTION 5

PLANS FOR FUTURE REPORTING PERIODS

This section outlines program plans for subsequent reporting periods. Particular emphasis will be placed on:

- Object model update, including velocity estimation
- Occlusion recognition and resolution
- Verification of the tracking algorithms through extensive simulation
- Target homing algorithms
- Critical aimpoint selection

We will investigate alternative methods for velocity estimation in order to obtain more robust estimators. This will allow us to perform occlusion prediction and background/target signature prediction. We will continue to do extensive simulation in order to verify the correctness of the tracking algorithms. We will develop a homing technique, based on our object models, which will allow the tracking of a target as the munition closes in and prevents drifting of the aimpoint. The critical aimpoint selection technique will be based on syntactic techniques demonstrated in the DARPA Automated Imagery Recognition System (AIRS) program by Honeywell.[2]

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[2] Contract No. F33615-76-C-1324.

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